

---

# TextLuas: Tracking and Visualizing Document and Term Clusters in Dynamic Text Data

---

**Derek Greene**

Insight Centre for Data Analytics  
University College Dublin, Ireland

**Daniel Archambault**

Department of Computer Science  
Swansea University, UK

**Václav Belák**

Insight Centre for Data Analytics  
NUI Galway, Ireland

**Pádraig Cunningham**

Insight Centre for Data Analytics  
University College Dublin, Ireland

## Abstract

For large volumes of text data collected over time, a key knowledge discovery task is identifying and tracking clusters. These clusters may correspond to emerging themes, popular topics, or breaking news stories in a corpus. Therefore, recently there has been increased interest in the problem of clustering dynamic data. However, there exists little support for the interactive exploration of the output of these analysis techniques, particularly in cases where researchers wish to simultaneously explore both the change in cluster structure over time and the change in the textual content associated with clusters. In this paper, we propose a model for tracking dynamic clusters characterized by the evolutionary events of each cluster. Motivated by this model, the TextLuas system provides an implementation for tracking these dynamic clusters and visualizing their evolution using a metro map metaphor. To provide overviews of cluster content, we adapt the tag cloud representation to the dynamic clustering scenario. We demonstrate the TextLuas system on two different text corpora, where they are shown to elucidate the evolution of key themes. We also describe how TextLuas was applied to a problem in bibliographic network research.

## 1 Introduction

In many domains, where the data has a temporal aspect, it will be of interest to analyze the formation and evolution of patterns in the data over time. For instance, researchers may be interested in tracking evolving communities of social network users, such as clusters of members with shared interests on social media sites. In the case of online news sources, each producing a substantial volume of articles on a daily basis, it will often be useful to chart the progress of individual news stories as they develop over time.

A number of authors have considered the problem of tracking clusters over time (Palla, Barabási and Vicsek, 2007; Greene, Doyle and Cunningham, 2010). Often these techniques involve dividing continuous data into a series of successive “time steps”, which can be analyzed in turn. However, these techniques have largely focused on the problem of finding dynamic communities in social networks. In addition, relatively little focus has been given to the problem of interactively visualizing cluster evolution – instead researchers have mostly relied on non-interactive diagrams of cluster evolution generated either manually or semi-automatically on small data sets (Palla et al., 2007; Tantipathananandh, Berger-Wolf and Kempe, 2007). In initial work on increasing the scalability of such methods, Rosvall and Bergstrom (2010) have emphasized the evolution of clusters over time. However, such techniques do not consider a key aspect of many dynamic data sets – the simultaneous

change in group memberships *and* in the textual content associated with clusters (*e.g.* frequent terms appearing in user-generated posts, popular tags appearing in social bookmarking sites).

In this paper, we seek to address the absence of a solution in this space, through the development of a methodology for simultaneously exploring both cluster evolution and content shifts in dynamic text data sets, where clusters correspond to themes or topics that develop over time. We propose that the dynamic data analysis task can be framed as the problem of tracking clusters of nodes in multiple related bipartite graphs. We present a model for tracking clusters over multiple time steps in a dynamic network, where the “life-cycle” of each cluster is characterized by a *timeline* indicating significant events. Using this model, we have developed a visualization system for exploring both evolving cluster timelines and the changing nature of their content. This system illustrates the relationship between dynamic clusters using a metro map-style layout, and the content contained in these clusters is presented in the form of aggregated tag clouds that are indicative of cluster content over a specific time period. The system, TextLuas, derives its name from the *Luas* tram service in Dublin, Ireland.

The remainder of the paper is structured as follows. In the next section, we provide a summary of relevant existing work pertaining to cluster analysis and visualizing dynamically evolving text and graphs. In section 3, we outline the proposed tracking model and provide a detailed description of the term cluster tracking method. While the proposed system can potentially be used independently of any specific clustering algorithm, in section 3.3 we discuss a suitable choice of algorithm which can be applied to identify co-clusterings in individual time steps, by taking into account both current and historic data. In section 4, we describe our visualization techniques. Results of our proposed visualization system on two real-world text collections, from economic news sources and a Web 2.0 social bookmarking portal, are discussed in section 5. Subsequently in section 5.3 we provide user feedback relating to the application of TextLuas by researchers interested in exploring bibliographic networks. The paper concludes with suggestions for plans for future work in the area of dynamic data analysis.

## 2 Related Work

### 2.1 Cluster Analysis

#### 2.1.1 Document Clustering

A wide range of algorithms have been proposed for the unsupervised exploration of text corpora (Ghosh, 2003). A common approach has been to apply partitioning algorithms, such as  $k$ -means or one of its many variants, to produce a disjoint partition of a document collection (Dhillon and Modha, 2001). An alternative approach to the document clustering problem is to “co-cluster” documents and terms simultaneously. Dhillon (2001) proposed representing a document collection as a weighted bipartite graph – the two node types in the graph correspond to terms and documents respectively, while edges between two nodes indicate how frequently a term occurs in a given document. The document clustering problem then involves partitioning the bipartite graph, which can be achieved efficiently by via a spectral approximation to the optimal normalized cut of the graph. Specifically, Dhillon (2001) proposed computing a truncated singular value decomposition (SVD) of a suitably normalized term-document matrix, constructing an embedding of both terms and documents, and applying  $k$ -means to this embedding to produce a simultaneous  $k$ -way partitioning of both documents and terms.

#### 2.1.2 Evolutionary Clustering

The general problem of identifying clusters in dynamic data has been studied by a number of authors. Early work on the unsupervised analysis of temporal data focused on the problems of topic tracking and event detection in document collections (Yang, Pierce and Carbonell, 1998). More recently, Chakrabarti, Kumar and Tomkins (2006) proposed a general framework for “evolutionary clustering”, where both current and historic information was incorporated into the objective function of the clustering process. The authors used this idea to formulate dynamic variants of common agglomerative and partitioning clustering algorithms. In the latter case, related clusters were tracked over time by matching similar centroids across time steps. Two evolutionary versions of spectral partitioning for classical (unipartite) graphs were proposed by Chi, Song, Zhou, Hino and Tseng

(2007). The first version (PCQ) involved applying spectral clustering to produce a partition that also accurately clusters historic data. The second version (PCM) involved measuring historic quality based on the chi-square distance between current and previous partition memberships. Both algorithms were applied to synthetic data and weekly blog link data. Recently, evolutionary approaches have been extended to the case of co-clustering – using bipartite spectral partitioning (Greene and Cunningham, 2010) and three-way matrix factorization (Peng and Li, 2011).

### 2.1.3 Dynamic Community Finding

The application of unsupervised dynamic data exploration methods has been particularly prevalent in the realm of social network analysis, where the goal is to identify groups representing communities of users in dynamic networks. Palla et al. (2007) proposed an extension of the popular *CFinder* clustering algorithm to identify community-centric evolution events in dynamic graphs, based on an offline strategy. This extension involved applying community detection to composite graphs constructed from pairs of consecutive time step graphs. The resulting clique-based communities are subsequently matched to communities in either of the individual time steps. Another life-cycle model was proposed by Berger-Wolf and Saia (2006), where the dynamic community finding approach was formulated as a graph coloring problem. The authors proposed a heuristic solution to this problem, by greedily matching pairs of node sets between time steps, in descending order of similarity. Asur, Parthasarathy and Ucar (2009) described a matching-based, cluster event identification strategy, which was implemented in the form of bit operations computed on time step community membership matrices. This strategy was applied to both bibliographic networks and clinical trial data in the context of pharmaceuticals.

## 2.2 Visualization

Our visualization approach encodes both cluster and topic evolution, emphasizing how the collection of clusters evolve over time. As a result, the technique draws on previous work in both text and dynamic graph visualization in a novel way to visualize the evolution of terms and clusters simultaneously. In section 2.2.1, we discuss several ways to visualize static and dynamic collections of unstructured text documents. Section 2.2.2 discusses methods for visualizing dynamically evolving communities.

### 2.2.1 Static and Dynamic Text Data

A number of works have looked at the problem of visualizing large collections of text documents in static and dynamic settings (Hearst, 2009). In this section, we cover a subset of these techniques that focus on visualizing the frequency of a term or theme without context in the collection of documents. Our visualization technique uses this work as a basis for visualizing word frequency data.

**Static context:** When summarizing word frequencies in a document or collection of documents, tag clouds are often used. Tag clouds have a history in varied domains including social psychology, literary works, finance, and web technologies (Viégas and Wattenberg, 2008). In a tag cloud, the frequency of a term or theme is mapped to the size of the word in the cloud, and these words are placed on several lines in the display. Variants of the tag cloud representation exists, Wordle<sup>1</sup> (Viégas, Wattenberg and Feinberg, 2009) for example, where the orientation of the words is freely chosen and words can be placed inside one another. As this is the most common method for visualizing term frequency in a document or collection of documents, we use the standard tag clouds to summarize the top terms in a cluster of documents and their aggregates.

**Tag cloud evaluation:** A number of user studies have looked at the effectiveness of tag clouds. A study (Rivadeneira, Gruen, Muller and Millen, 2007) presented two experiments that evaluated tag cloud properties such as font size and word order. The authors found that words with larger font sizes were recalled more easily and that when words were organized according to frequency, participants were better able to form an impression about the subjects discussed in the document. A second experiment (Halvey and Keane, 2007) also investigated the time taken to find words in a tag cloud. The experiment found that larger tag sizes and an alphabetical ordering of the tags decreased task completion time. Alphabetically ordered lists of words outperformed alphabetically ordered

---

<sup>1</sup><http://www.wordle.net>

tag clouds in terms of completion time for this task. In TextLuas, we support both frequency and alphabetical orderings.

**Dynamic context:** Often, how a term or a set of terms evolve over time is the focus of analysis. In these cases, time is encoded spatially, often as a flow from left to right, and the frequency of terms are encoded on the vertical axis. ThemeRiver (Havre, Hetzler, Whitney and Nowell, 2002) expresses the frequency of a term or theme over time. Each theme is given its own color and stream thickness encodes frequency. As time flows from left to right, the changes in thickness encode the changes in frequency. The NameVoyager (Wattenberg, 2005) was designed in a similar way. In the tool, time flows left to right and the thickness of streams indicate the frequency of names given to children born that year. However, neither system encodes dynamic cluster structure and instead focuses on term/name evolution only.

## 2.2.2 Dynamic Community Visualization

As noted in section 2.1.3, a common application of dynamic clustering methods has been in the task of finding communities in social networks. When the number of communities and the size of each community is small or medium-sized, visualization techniques exist to examine how the topologies of those communities evolve over time (Frishman and Tal, 2004) or diagrams that depict the evolution of community structures (Tantipathananandh et al., 2007). However, neither method directly handles terms associated with each community, and the representations can have difficulty scaling data sets with larger community sizes and a larger number of communities.

More abstract representations of communities and their structure are often needed to allow visualizations to scale to a larger number of communities. Falkowski, Bartelheimer and Spiliopoulou (2006) creates a node for each community. The x-coordinate of that node corresponds to its time period. The y-coordinate is computed based on similarity to other communities at that time and directed edges connect communities in adjacent time periods to describe community evolution. Alluvial diagrams (Rosvall and Bergstrom, 2010) depict each community as a line swath whose width is proportional to its number of members. Gaps are placed between time periods and the swaths split and merge as the communities evolve over time. On the other hand, Yang, Asur, Parthasarathy and Mehta (2008) present a visual analytics system that is more topology-centric. An overview of all major events in community evolution is presented, and the user of the system can click on elements of this list to view what happened to the community before and after the event.

This previous work either employs a topology-centric (Frishman and Tal, 2004; Yang et al., 2008) or an evolution-centric (Falkowski et al., 2006; Tantipathananandh et al., 2007; Rosvall and Bergstrom, 2010) approach for depicting community evolution, by using spatial position to encode either community topology or evolution respectively. In our approach, we start with a evolution-centric view of the data. However, because we only deal with clusters of documents and terms, we are able to provide summaries, in terms of textual content of the clusters, through tag clouds.

## 3 Methods

### 3.1 Overview

In the offline formulation of the dynamic co-clustering problem, our overall goal is to identify a set of *dynamic clusters*, represented as linear timelines extending across multiple time steps. *Step clusters* are the clusters identified at individual time steps. These represent specific observations of dynamic clusters at a single point in time. The offline dynamic text co-clustering problem has three key requirements:

1. An approach to aggregate step clusters into dynamic cluster timelines, and track these dynamic clusters across time steps. Based on our previous work in social network analysis (Greene et al., 2010), we propose a framework for tracking clusters in dynamic text data in section 3.2, and describe a specific implementation of the framework in section 3.2.4.
2. A suitable algorithm to cluster individual time step graphs. We briefly describe a suitable choice of algorithm in section 3.3.

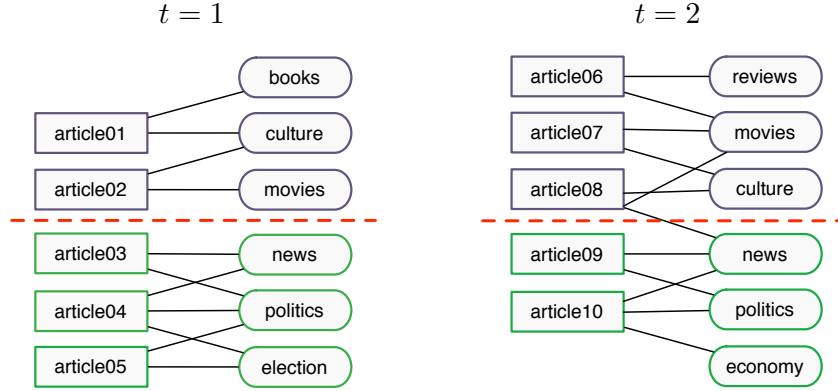


Figure 1: Example of a dynamic text data set, which consists of two time steps, ten documents, and eight unique terms. The data set is represented in the form of two bipartite graphs, showing the presence of terms in documents in both time steps. Note that a subset of terms alone persist between the two time steps. A trivial partitioning of both documents and terms across the two time steps is indicated by the dashed line.

3. An appropriate technique to visualize dynamic cluster timelines, highlighting both events in the evolution of clusters and representative cluster content. In section 3.4 we describe the problem of generating content summaries for clusters. The visualization techniques are discussed in section 4.

## 3.2 Tracking Dynamic Clusters

### 3.2.1 Problem Formulation

As described in section 2.1.1, previous work by Dhillon (2001) involved representing a static text data set in the form of a single weighted bipartite graph. Documents and terms can then be co-clustered by partitioning the nodes of the bipartite graph. For the case of dynamic text data, where we are following an offline strategy, a complete corpus can be represented as a set of  $l$  bipartite graphs  $\{G_1, \dots, G_l\}$ , where each graph is built from the documents collected during a single time step. The duration of the time step controls the “resolution” at which we intend to explore the data. Each *step graph*  $G_t$  consists of two distinct sets of nodes, representing the  $m_t$  terms and  $n_t$  documents present in the data at time  $t$ . Clustering each step graph yields a set of *step clusters*. These clusters contain both terms and documents, and may be disjoint or overlapping. The dynamic clustering task involves identifying a set of *dynamic clusters* built from step clusters observed at different time steps.

In some domains, both data objects and features will persist over time. However, for text-based data it will generally be the case that documents will only exist at given point in time (*e.g.* the publication date for news articles, research papers), while many terms will persist in the data over time. Therefore, while step clusters contain both terms **and** documents, we propose tracking dynamic clusters (*i.e.* connecting step clusters) based on terms alone. These terms represent indicative keywords that define a particular theme, topic, or news story across time.

An illustrative example is shown in Fig. 1, where a dynamic text data set is represented by two bipartite graphs corresponding to two discrete time steps. In each bipartite graph there is a trivial partitioning of both documents and terms into two clusters. By matching clusters via the subset of terms common to the two graphs, we can readily see that the two topical clusters persist across both time steps. These represent dynamic clusters in the data.

### 3.2.2 Dynamic Cluster Timelines

We would like to define a convenient structure for representing the history and development of dynamic clusters in a data set. Firstly, we denote the set of  $k'$  dynamic clusters as  $\mathbb{D} = \{D_1, \dots, D_{k'}\}$ ,

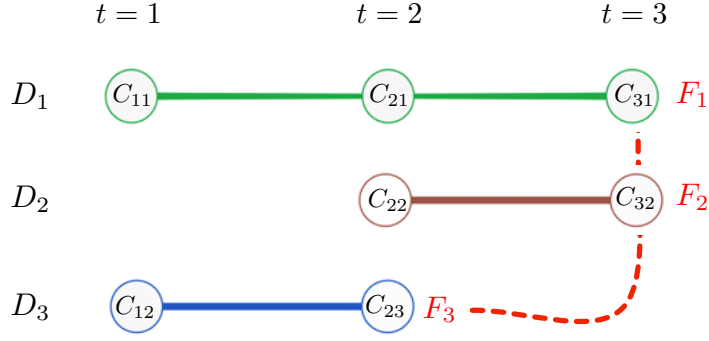


Figure 2: Example of three dynamic cluster timelines tracked over three time steps, featuring continuation, birth, and death cluster life-cycle events. The dynamic cluster *fronts* are highlighted. These represent the most recent observations of the dynamic clusters.

and denote the set of  $k_t$  step clusters identified at time  $t$  as  $\mathbb{C}_t = \{C_{t1}, \dots, C_{tk_t}\}$ . Consequently, each dynamic cluster  $D_i$  can be represented by a *timeline* of its constituent step clusters, ordered by time, with at most one step cluster for each time  $t$ .

Fig. 2 shows a simple example involving three step clusterings containing observations of three distinct dynamic clusters. The timelines for these three dynamic clusters are straight-forward:

- $D_1: \{C_{11}, C_{21}, C_{31}\}$
- $D_2: \{C_{22}, C_{32}\}$
- $D_3: \{C_{12}, C_{23}\}$

A more complex scenario is shown in Fig. 3. Note that, while there appear to be three distinct branches at time  $t = 3$ , there are in fact four dynamic clusters with four corresponding timelines as follows:

- $D_1: \{C_{11}, C_{21}, C_{31}\}$
- $D_2: \{C_{12}, C_{21}, C_{31}\}$
- $D_3: \{C_{13}, C_{22}, C_{32}\}$
- $D_4: \{C_{13}, C_{23}, C_{33}\}$

The most recent observation in a timeline is referred to as the *front* of the dynamic cluster. The front for  $D_i$  is denoted  $F_i$ . The fronts for the three dynamic clusters are highlighted in Fig. 2. Note that the dynamic cluster  $D_3$  does not have a corresponding observation at time  $t = 3$ , so its front is the step cluster  $C_{23}$  from the previous time  $t = 2$ .

### 3.2.3 Dynamic Cluster Events

When exploring the themes or topics present in a document collection, we would like to examine their development over time and the relationships between them. Based on the timeline structures, we can characterize the evolution of dynamic clusters in terms of a number of fundamental cluster “life-cycle” events:

- *Birth*: The emergence of a step cluster  $C_{tj}$  observed at time  $t$  for which there is no corresponding dynamic cluster in  $\mathbb{D}$ . A new dynamic cluster  $D_i$  containing  $C_{tj}$  is created and added to  $\mathbb{D}$ . An example in Fig. 2 is the cluster  $D_2$  born in the second time step.
- *Death*: The dissolution of a dynamic cluster  $D_i$  occurs when it has not been observed (*i.e.* there has been no corresponding step cluster) for at least  $d$  consecutive time steps.  $D_i$  is subsequently removed from the set  $\mathbb{D}$ . An example in Fig. 2 is  $D_3$ , assuming that no further step clusters are subsequently assigned to its timeline.

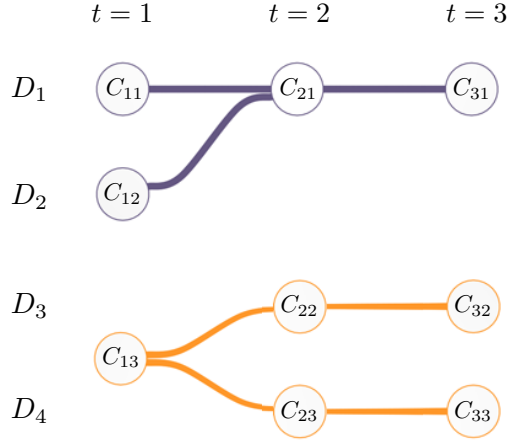


Figure 3: Example of four dynamic cluster timelines over three time steps, illustrating merge and split life-cycle events.

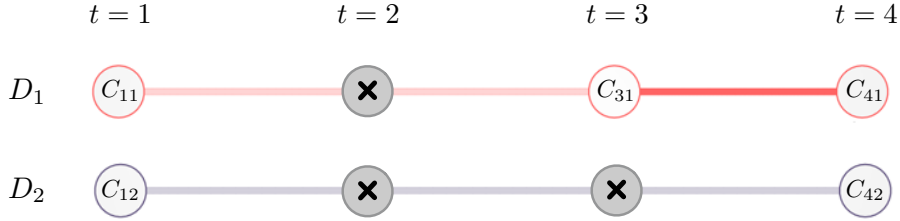


Figure 4: Example of two “intermittent” dynamic clusters which are not observed at every time step after birth. The dynamic cluster  $D_1$  is unobserved in the graph at time  $t = 2$ , but continues in time step  $t = 3$ , while the dynamic cluster  $D_2$  is missing from both  $t = 2$  and  $t = 3$ .

- *Merging*: A merge occurs if two distinct dynamic clusters ( $D_i, D_j$ ) observed at time  $t - 1$  match to a single step cluster  $C_{ta}$  at time  $t$ . The pair subsequently share a common timeline starting from  $C_{ta}$ . In Fig. 3 the dynamic clusters  $D_1$  and  $D_2$  are both matched to  $C_{21}$  in the second step.
- *Splitting*: It may occur that a single dynamic cluster  $D_i$  present at time  $t - 1$  is matched to two distinct step clusters ( $C_{ta}, C_{tb}$ ) at time  $t$ . A branching occurs with the creation of an additional dynamic cluster  $D_j$  that shares the timeline of  $D_i$  up to time  $t - 1$ , but has a distinct timeline from time  $t$  onwards. In Fig. 3 an existing dynamic cluster  $D_3$  is matched to both  $C_{22}$  and  $C_{23}$  in the second step, resulting in the creation of an additional dynamic cluster  $D_4$ .

In most cases, we will observe trivial *continuation* events, where a dynamic cluster observed at time  $t$  also has an observation at time  $t + 1$ . However, note that a dynamic cluster may not necessarily be observed at all time steps after birth – it may be observed at birth time  $t$  and at death time  $t' > t$ , but may be missing from one or more intermediate steps (but less than  $d$  consecutive steps) between  $t$  and  $t'$ . Two examples are shown in Fig. 4. This reflects the idea that temporally “intermittent” clusters can exist in the data. For instance, in the case of mainstream news data, a story may receive considerable coverage for a short period of time, coverage may then cease and subsequently recommence at a later date when there are further developments relating to the story. The frequency of appearance of such intermittent behavior will often depend on the duration of each time step.

### 3.2.4 Tracking Clusters Across Time Steps

The model presented above describes a general framework for representing dynamic clusters, in the form of timelines of step clusters that highlight cluster life-cycle events. Given a set of bi-

partite graphs representing a complete dynamic text data set, we now propose a simple approach for constructing such timelines. The key issue in this task concerns how best to match step clusters at a given time  $t$  to the existing set of dynamic clusters  $\mathbb{D}$ . To address this issue, we employ a heuristic threshold-based matching method, which allows for many-to-many mappings between clusters across different time steps. This mapping supports the identification of dynamic events such as cluster merging and splitting. As noted previously, although we cluster terms and documents at each step, we intend to track dynamic clusters based on terms persisting across different time steps. Therefore, the mappings are calculated solely based on the term-cluster memberships in step clusterings.

The proposed approach proceeds as follows. The first step clustering  $\mathbb{C}_1$  of terms and documents is generated by applying a suitable clustering algorithm (such as that described next in section 3.3) to the bipartite graph  $G_1$ . We use this graph to bootstrap the process. A distinct dynamic cluster is created from the term memberships for each step cluster. The next step clustering  $\mathbb{C}_2$  is generated by clustering the bipartite graph  $G_2$ . We then attempt to match these step clusters with the dynamic cluster fronts  $\{F_1, \dots, F_{k'}\}$  (i.e. the step clusters from  $\mathbb{C}_1$ ). All pairs  $(C_{2a}, F_i)$  are compared, and the dynamic cluster timelines and fronts are updated based on the event rules described previously in section 3.2. The process continues until all  $l$  step graphs have been processed.

To perform the actual matching, we employ the widely-used Jaccard coefficient for binary sets (Jaccard, 1912). Given a step cluster  $C_{ta}$  and a dynamic cluster front  $F_i$ , the similarity between the pair is calculated as:

$$\text{sim}(C_{ta}, F_i) = \frac{|T_{ta} \cap F_i|}{|T_{ta} \cup F_i|} \quad (1)$$

where  $T_{ta}$  denotes the set of terms in the step cluster  $C_{ta}$ . If the similarity exceeds a matching threshold  $\theta \in [0, 1]$ , the pair are matched, and  $C_{ta}$  is added to the timeline for the dynamic cluster  $D_i$  corresponding to  $F_i$ .

The output of the matching process between a step clustering  $\mathbb{C}_t$  and the existing fronts  $\{F_1, \dots, F_{k'}\}$  will implicitly reveal a series of cluster evolution events. A step cluster  $C_{ta}$  matching to a single dynamic cluster indicates a continuation, while the case where  $C_{ta}$  matches multiple dynamic clusters results in a merge event. If no suitable match is found for  $C_{ta}$  above the threshold  $\theta$ , a new dynamic cluster is created for  $C_{ta}$ .

### 3.3 Clustering at Individual Time Steps

Previously we have described an approach for constructing dynamic cluster timelines from collections of step clusters. We also require a suitable clustering algorithm to produce a clustering of each step graph. One option is to apply an existing clustering or community-finding algorithm on a unipartite representation of the data, and then derive term memberships from these groups and the original data (e.g. by examining term-centroid weights). An alternative is to apply a co-clustering approach to cluster both documents and terms simultaneously (Dhillon, 2001). However, previous work has shown that there are advantages to clustering techniques that also consider historic information, rather than taking a static approach which treats each time step entirely in isolation (Chakrabarti et al., 2006).

We have previously introduced a dynamic spectral co-clustering algorithm (Greene and Cunningham, 2010). This algorithm takes into account both information from a spectral embedding of the current bipartite graph, together with historic information from the previous time step. Evaluations performed on news and social media data sets showed that the algorithm is effective in accurately identifying coherent clusters, while also ensuring a consistent transition between clusterings in successive time steps. In this section, we provide a general overview of the algorithm, and apply it as part of our system evaluation in sections 5.1 and 5.2.

Firstly, we represent the bipartite graph  $G_t$  for step  $t$  as a rectangular adjacency matrix  $\mathbf{A}_t$  of size  $m_t \times n_t$ , with rows corresponding to terms and columns corresponding to documents. We construct the degree-normalized adjacency matrix  $\hat{\mathbf{A}}_t = \mathbf{D}_1^{-\frac{1}{2}} \mathbf{A}_t \mathbf{D}_2^{-\frac{1}{2}}$ , where  $\mathbf{D}_1$  and  $\mathbf{D}_2$  are diagonal column and row degree matrices respectively. We then apply SVD to  $\hat{\mathbf{A}}_t$ , computing the leading left and right singular vectors corresponding to the largest singular values. We use  $k_t$  singular vectors, corresponding to the expected number of clusters for the time step. The truncated SVD yields



matrices  $\mathbf{U}_{\mathbf{k}_t}$  and  $\mathbf{V}_{\mathbf{k}_t}$ . A unified embedding of terms and documents is constructed by normalizing and stacking the truncated factors as follows:

$$\mathbf{Z}_t = \begin{bmatrix} \mathbf{D}_1^{-1/2} \mathbf{U}_{\mathbf{k}_t} \\ \mathbf{D}_2^{-1/2} \mathbf{V}_{\mathbf{k}_t} \end{bmatrix} \quad (2)$$

Prior to clustering, the rows of  $\mathbf{Z}_t$  are subsequently re-normalized to have unit length, as proposed by Ng, Jordan and Weiss (2001). The rows of this matrix provide a  $k_t$ -dimensional embedding of all terms and documents present in  $G_t$ .

At time  $t = 1$ , we have no historic information. So we generate a step clustering by applying  $k$ -means to the embedding  $\mathbf{Z}_1$ , using orthogonal initialization (Ng et al., 2001). For  $t > 1$ , we wish to initialize using clusters from the previous time step. Since we assume that only a subset of terms will persist between time steps, we will not have initial cluster memberships for any documents, and may also lack memberships for some terms that were not present in the last step. Therefore, we predict initial cluster memberships for each unassigned row  $z_i$  of  $\mathbf{Z}_t$ , using a simple nearest centroid classifier trained on the centroids constructed from rows of  $\mathbf{Z}_t$  for which membership information is available. This yields a predicted clustering  $\mathcal{P}_t$  based on historic information.

Once we have initialized the clustering process with  $\mathcal{P}_t$ , we apply a constrained version of  $k$ -means clustering to the rows of the embedding  $\mathbf{Z}_t$ , taking into account both the internal quality of the current partition and agreement with the predicted partition  $\mathcal{P}_t$ . To combine both sources of information, the clustering objective becomes a weighted combination of two quality measures:

$$J(\mathcal{C}_t) = (1 - \alpha) \cdot \left( \sum_{c=1}^k \sum_{z_i \in C_c} z_i^\top \mu_c \right) + \alpha \cdot (\text{pred}(\mathcal{P}_t, \mathcal{C}_t)) \quad (3)$$

The first term in Eqn. 3 represents the standard spherical  $k$ -means objective (Dhillon and Modha, 2001), while in the second term,  $\text{pred}(\mathcal{P}_t, \mathcal{C}_t)$  denotes the pairwise agreement between the predicted clustering  $\mathcal{P}_t$  and the current clustering. The parameter  $\alpha \in [0, 1]$  controls the balance between the influence of the information present in the current spectral embedding and the historical information. A higher value of  $\alpha$  allows information from the previous time step to have a greater influence. The output of the constrained  $k$ -means process is a co-clustering of the terms and documents in  $G_t$ .

### 3.4 Post-Processing for Visualization

#### 3.4.1 Building Tag Clouds

As described in section 2.2, one way to summarize a collection of text data is to use a tag cloud. In this paper, we use tag clouds to present an overview of the content in a single step cluster or the aggregate content of multiple step clusters (*e.g.* the step clusters from one or more dynamic clusters.). The visualization technique will be further described in section 4.

In its most fundamental form, the data represented in a tag cloud consists of a set of unique terms (*i.e.* the tags) with a corresponding set of weights, indicating the relative importance of each term. These weights are used to control the prominence of each term in the cloud. To identify the set of descriptive terms for each step cluster, we use a variant of the centroid-based ‘‘concept decomposition’’ method proposed by Dhillon and Modha (2001). For a step cluster  $C_{ta}$  containing terms and documents, we calculate the term weights as follows:

1. Based on the documents assigned to  $C_{ta}$ , compute the centroid vector  $w_{ta}$  from the term-document frequency values in the corresponding step graph  $G_t$ .
2. Set all entries in  $w_{ta}$  to zero, with the exception of those entries corresponding to the terms assigned to  $C_{ta}$ .
3. The terms with the highest non-zero weights in  $w_{ta}$  are used to produce the tag cloud representing the content in  $C_{ta}$ .

#### 3.4.2 Aggregating Tag Clouds

To generate a tag cloud describing the aggregate content for two or more step clusters, we construct a weight vector for each cluster as described above and compute the mean vector  $\bar{w}$ . The highest-

weighted terms in  $\bar{w}$  provide the tags for the aggregate cloud. In this way, we can summarize the content of part or all of a dynamic cluster timeline.

## 4 Visualization

The model and the output of the dynamic clustering approaches, discussed in section 3.2, naturally leads toward visualization techniques which explicitly encode timelines. Visualizations, structured in this way, would provide a life-cycle perspective of the data. In our case, we employ a “metro map” metaphor to depict dynamic cluster evolution.

The visualization is composed of three components. The first two components, presented in Fig. 5, provide overviews of cluster evolution. The set of cluster timelines on the left, depicting the events in the evolution of timelines, is the *metro map view*, which is discussed in section 4.1. On the right of this same display is the *matrix of summary tag clouds*. These summaries, discussed in section 4.2, have the same color of the line that they represent and have a tag cloud that encodes the average frequency of the terms on that line. Clicking on any tag cloud in this matrix, brings up the *metro line details*. This view, shown in Fig. 8, provides details for a single timeline or the parts of the metro map that are in the same color. This view is discussed in section 4.3.

Our system heavily relies on linked views (North and Shneiderman., 2000). Linked views have the advantage of maximizing the readability of the summary tag clouds and the textual content in the details view. Integrating the tag clouds into a single visualization would have the advantage that only a single view would be required for visualizing the data. However, they would have the disadvantage that reading the textual content of a large number of timelines would be difficult.

### 4.1 Metro Map View

The metro map view shows the dynamic cluster timelines for a complete dynamic text data set, through the use of a metro map metaphor. In this view, time progresses from left to right, with  $t = 1$  being in the leftmost part of the diagram. Initially, all lines are colored gray. The user of the system can select metro lines to change their color. Summaries of these lines are added to the summary tag cloud matrix. The next two sections describe how this diagram is drawn, and how users interact with it.

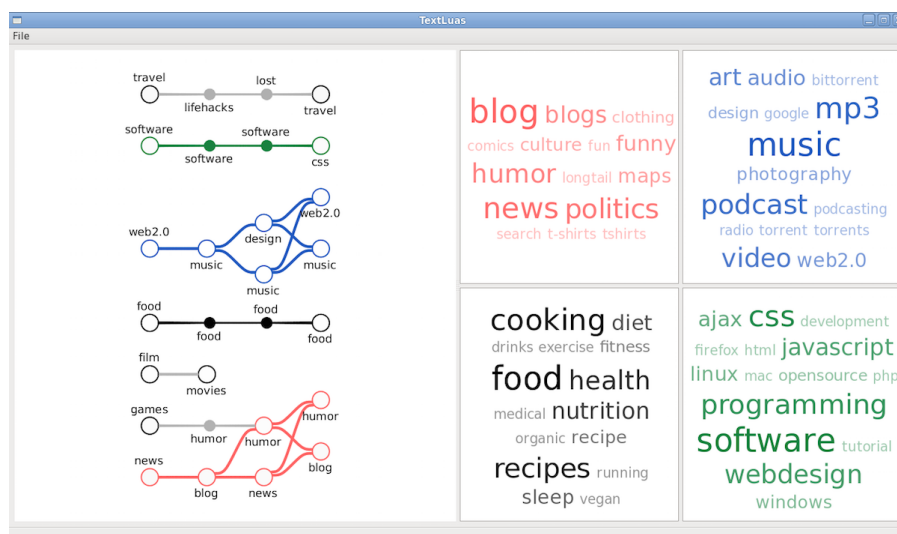


Figure 5: TextLuas main interface. The left side of the screen is the metro map view which depicts the dynamic clusters. The right side of the screen is the matrix of summary tag clouds which summarizes the terms present in each line.

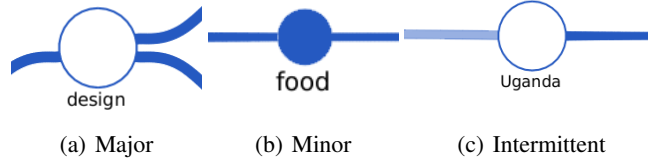


Figure 6: Encoding for major stations, minor stations, and intermittent lines. **(a)** Major station is depicted as a hollow circle. **(b)** Minor station is depicted as a solid circle. **(c)** Intermittent lines have a lower alpha value than lines which represent continuation. In this subfigure, the left line is intermittent while the right line is not.

#### 4.1.1 Diagram Rendering and Encoding

In our metaphor, step clusters are indicated by “stations”. A directed edge connects two step clusters if they appear successively in the same timeline. Thus, the topology of any dynamic cluster timeline is always a directed acyclic graph (DAG), as edges are always oriented in the direction of increasing time (left to right in our diagrams). The problem of drawing DAGs is well-studied, with many algorithms existing to generate useful drawings. In this work, we use the algorithm implemented in the Tulip framework (Auber, 2003) as a basis for diagram generation. All metro map style drawings in this paper are also rendered using Tulip.

We would like to ensure that all step clusters co-occurring at the same time  $t$  are vertically aligned. As dynamic clusters can be born, become intermittent, and die at any time, for the purposes of diagram layout we need to insert dummy nodes. For birth events that happen at times  $t > 1$ , we prefix the birth event with a series of dummy nodes. For intermittent events, we connect the last time the cluster was observed to the next time the cluster is observed with a series of dummy nodes (the nodes marked “x” in Fig. 4). For deaths, we do not insert dummy nodes after the last observation of the cluster and the algorithm places the node at the correct level. Dummy nodes are inserted for the purposes of diagram layout, but these nodes are removed before diagram display.

When an edge connects two nodes that are not horizontally aligned, it is represented as a smoothly interpolating spline curve. The line-projected control points of this spline curve are placed procedurally according to the distance between the stations. For stations  $(x_1, y_1)$  and  $(x_2, y_2)$  with the vector between them  $(a, b)$ , the two control points are placed at  $(x_1 + a/3, y_1 + b/6)$  and  $(x_2 - a/3, y_2 - b/6)$ . If the degrees of the nodes in the diagram are relatively low, this heuristic allows edges smoothly bend into and out of stations.

In the diagram, there are major stations and minor stations. A *major station* corresponds to a step cluster at which a life-cycle event occurs: birth, death, merge, split, or begin/end of an intermittent period. Major stations are drawn as hollow circles as shown in Fig. 6(a). *Minor stations* correspond to step clusters that are continuation events. They always have an in degree of one and an out degree of one and are not adjacent to any dummy nodes. These stations are encoded as filled circles as shown in Fig. 6(b). When a dynamic cluster becomes intermittent, its edge is rendered with a higher alpha value as shown in Fig. 6(c). Stations, by default, are named with the term that is the most prevalent in its cluster. However, the user of the system can specify a “names” file as input for custom station names that would be more useful for their task. For split and merge events, this label is always placed beneath the node. For all other stations, the label placement alternates between above and below the station in the depiction of the dynamic cluster.

#### 4.1.2 Interaction

As selecting all stations individually can be time consuming, selection and deselection of stations and edges in the TextLuas is propagated rightward following the direction of the edges. Fig. 7(a) shows part of the metro map. By clicking on the node labeled “music” at  $t = 2$ , the entire subtree connected to the right of “music” is selected as shown in Fig. 7(b). Subtrees can be removed from the selection in a similar way. Fig. 7(c) shows the result after the edge between “music” ( $t = 2$ ) and “music” ( $t = 3$ ) was clicked, removing that subtree from the selection. If the user would like

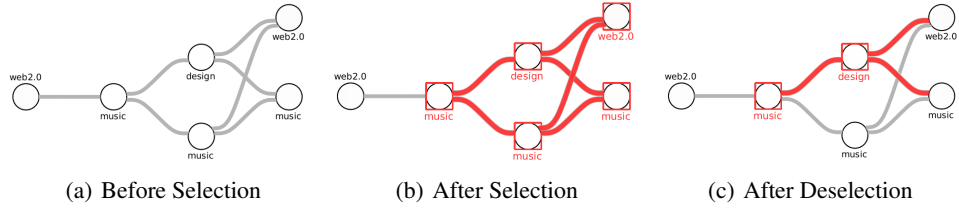


Figure 7: Figure showing flood selection in TextLuas. **(a)** Unselected portion of the metro map. **(b)** After clicking on “music” at time 2, all nodes rightward and connected to “music” are selected. **(c)** After clicking on the edge between “music”  $t = 2$  and “music”  $t = 3$ , the lower subtree is deselected. The leaves, “music” and “web2.0”, can be re-added to the selection by clicking on them individually.

to re-add the nodes “music” and “web2.0” at  $t = 4$ , they can be selected manually. Once the user is happy with their selection, they simply press a number key to color the entire selection. It is important to note that selections do not need to be connected.

Initially, all lines in the diagram are colored gray. When a metro line takes on a color, its corresponding tag cloud is placed in the summary of tag clouds matrix with all nodes colored the same color as the metro line.

## 4.2 Matrix of Summary Tag Clouds

The matrix of summary tag clouds presents an overview of the topics discussed on each colored timeline of the TextLuas. Tag size is based on the term weighting strategy described in section 3.4, using the mean of the weight vectors for all step clusters assigned that color. The terms of the tag clouds can be ordered either alphabetically or by frequency to better support a wider range of tasks. To see the details of a line, the user simply clicks on the tag cloud to bring up the metro line details view, which is discussed in the next section.

## 4.3 Metro Line Details

The metro line details view provides a more comprehensive summary of the content and evolution of the metro line (*i.e.* dynamic cluster timeline) of a particular color. In this view, the user can explore the details of paths on the line, and the details of the terms at each station. Fig. 8 shows the interface, where the top of the screen is the path view and the bottom is the station cloud matrix.

### 4.3.1 Path View

The path view shows all stations of a particular color and how they interconnect with one another. When the view is launched, a single path is highlighted in the display. Using the up and down arrow keys, the user can browse through the paths in the diagram in a depth first traversal order. For each station highlighted in this view, information is displayed in the station cloud matrix. In the top of Fig. 8, the blue line is shown. Currently the path highlighted in  $t \in [1, 4]$  is “web 2.0”, “music”, “design”, and “music”.

### 4.3.2 Station Cloud Matrix

The station cloud matrix is a small multiples (Tufte, 1990) view – a matrix of images shows the differences between objects at the given times, depicting dynamic evolution along that path. The user of the system can click on any tag in any of the station clouds to reveal how that tag evolves in prominence through time. In Fig. 8, the term “podcast” has been double clicked, revealing how it evolves down this line. Notice that “podcast” is not present in the third time step, and this fact is made immediately apparent using the pre-attentive nature of color. Recent experiments have shown that for multi-dimensional data (probably the closest type of data to the information we want to visualize per cluster), small multiples seems to be better in terms of human performance (Robertson,

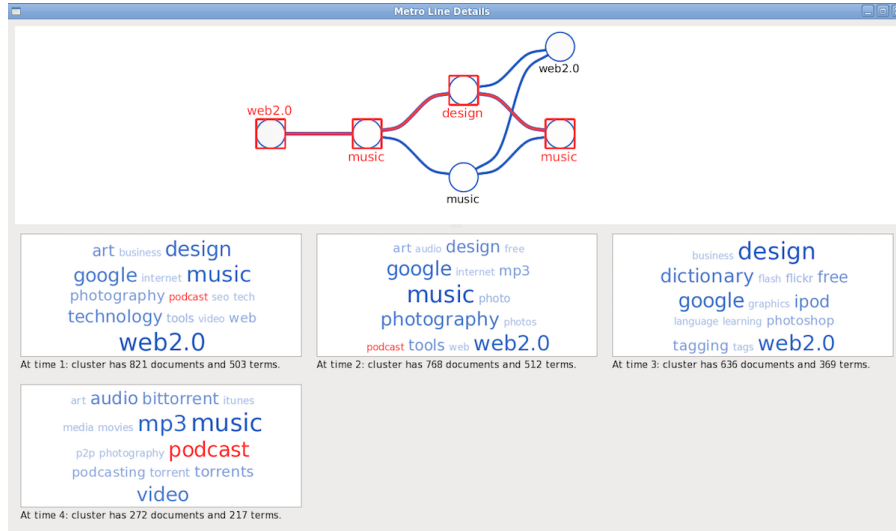


Figure 8: Metro line details view. The display shows the metro line of the selected color and highlights a path through it in the top half of the display. In the bottom half of the display, a small multiples view of the data at each station along the highlighted path is shown. Linked highlighting between the station clouds indicate the evolution of importance of a term. In this example, “podcast” is highlighted in all stations except station three where it falls out of prominence.

Fernandez, Fisher, Lee and Stasko, 2008). Therefore, we chose this representation over an animated tag cloud.

In the current tag cloud view, details for the highlighted path are shown. The number of documents and terms for the current step cluster are printed at the bottom of the tag cloud display. The largest term in the tag cloud corresponds to the station name, but for the remaining tags, the small multiples view displays how the term frequency varies along the path. For example, we notice that “photography” is a popular term at  $t \in [1, 2]$ , but becomes less prominent in  $t \in [3, 4]$ . Also, the term “video” suddenly emerges at  $t = 4$ , when it was not present at any other time. At most six station tag clouds are displayed at a time. The left and right arrow keys return/advance to the previous/next stations on the line.

## 5 Results and Discussion

In this section, we present use cases for the TextLuas system in terms of its capacity to visualize dynamically evolving clusters using the techniques described in section 4. The experiments are performed on two real-world corpora containing time-stamped documents. The corpora and system implementations are available online<sup>2</sup>. Subsequently, in section 5.3, we provide user feedback based on an application of TextLuas to the exploration of the evolution of scientific communities via the analysis of dynamic bibliographic data.

### 5.1 Social Bookmarking Data

In our first case study, we considered a Web 2.0 data exploration problem, where a collection of bookmarked websites has been manually assigned terms or tags by a community of users over time. For the purpose of clustering, each site can be described using a “bag of tags” text representation. The goal is to cluster sites and terms to explore the changing nature of user interests. Note that, while some bookmarked sites may persist over time, we focus here on tracking dynamic clusters based on terms alone, as described in section 3.2.

<sup>2</sup><http://mlg.ucd.ie/textluas>

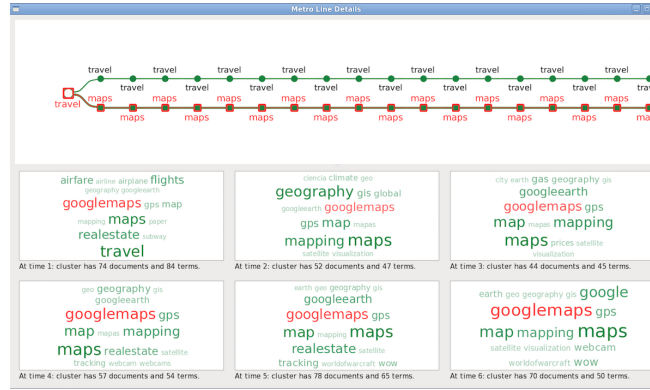
We use a subset of the most recent data from a bookmark collection harvested by Görlitz, Sizov and Staab (2008) from the *Del.icio.us* web portal. The subset covers the 2,000 top tags and 5,000 top sites across an eleven month period from January to November 2006. We divided this period into 44 weekly time steps, and, for each time step, we constructed a bipartite graph. The two node types correspond to terms (tags) and sites, and edges denote the number of times each site was assigned a given term during the time step. On average, each graph contained approximately 3750 sites and 1760 terms. Prior to clustering, vectors representing sites were normalized to unit length. No further normalization or term weighting was applied. Following initial experiments on the data (Greene and Cunningham, 2010), we set  $k_t = 20$  to identify high-level topical clusters, and used a balance parameter of  $\alpha = 0.1$  to allow a contribution from historic data, without overly constraining the co-clustering process. We examined a range of low matching thresholds  $\theta \in [0.1, 0.3]$ . The general content of the resulting timelines was not significantly different for these values. As representative results, we show the timelines identified for  $\theta = 0.2$ .

When applied, the TextLuas metro map view shows us that the *Del.icio.us* data set contains relatively distinct topics that persist through time. Dynamic clusters are generally born at  $t = 1$  (January 2006) and continue until  $t = 44$  (November 2006). This property is perhaps unsurprising, given that the data pertains to popular websites and tags – we would expect that user-selected terms like “shopping” and “travel” will continue to be popular over time. Fig. 9 shows a number of the most persistent timelines. On the left-hand side, we see the timelines, zoomed to focus on a two-month period. The largely disjoint nature of the timelines is apparent. However, we did observe a small number of other life-cycle events in the data. For instance, there is a divergence in the dynamic cluster labeled “travel.” This split creates two timelines: one focusing on travel & airlines and the other on mapping & geography. We can use the metro line details view described in section 4.3 to view details of this split and its two resulting dynamic clusters. Figures 10(a) and 10(b) show the difference in the content between the two timelines. The content of the station clouds suggests that the split appears to correspond to the increasing popularity of Google Maps during early 2006. Linked highlighting between station tag clouds indicates that the keyword *googlemaps* is consistently popular in the “Maps” timeline but only appears in the splitting station of the “Travel” timeline, illustrating the shift in topic.

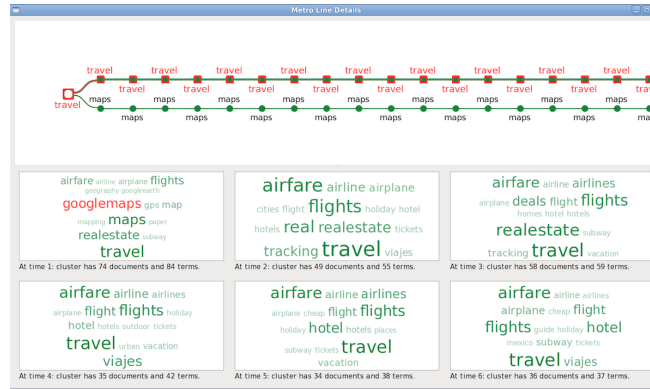
Although the station labels in Fig. 9 appear relatively static, and the majority of dynamic clusters continue uninterrupted from birth to death, we would expect there to be constant smaller changes in the popularity of bookmarks and terms between steps. To illustrate this fact, we again consult the metro line details view. In Fig. 11 we show the station cloud matrix for a dynamic cluster related to “shopping”. Although the cluster’s timeline has the same station label for all time steps in the metro map view, the clouds, shown in Fig. 9, provide a far more detailed representation of the content



Figure 9: A subset of dynamic cluster timelines identified on the *Del.icio.us* data set. The left-hand side shows the metro map view of the timelines over an 8 week period. The right-hand side shows aggregate tag clouds for the four selected paths.



(a) “Maps” timeline



(b) “Travel” timeline

Figure 10: TextLuas metro line details view in the *Del.icio.us* data set. By pressing the arrow keys, we can alternate between the dynamic cluster above and below the split. The top line contains topics on mapping & geography while the bottom contains topics on travel. Linked highlighting between the station clouds indicates that the term *googlemaps* is a popular tag in the “Maps” timeline but is not present in the “Travel” timeline at all, except for at the split event.

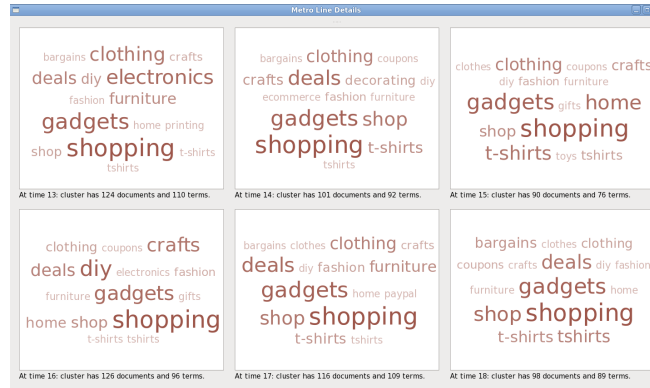


Figure 11: A station cloud matrix of metro line details, representing a dynamic cluster related to “shopping” in the *Del.icio.us* data set. The tag clouds illustrate the changing content of the dynamic cluster over six time steps.



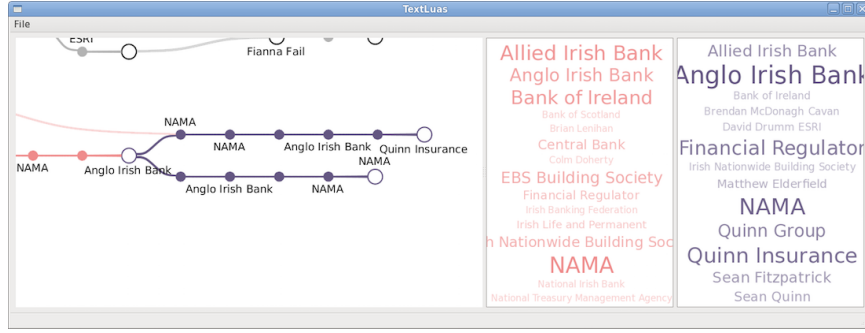


Figure 12: Metro map view of a number of timelines identified on the Irish economic news data set. Several cluster life-cycle events are apparent: continuation, merging, splitting, and intermittent behavior.

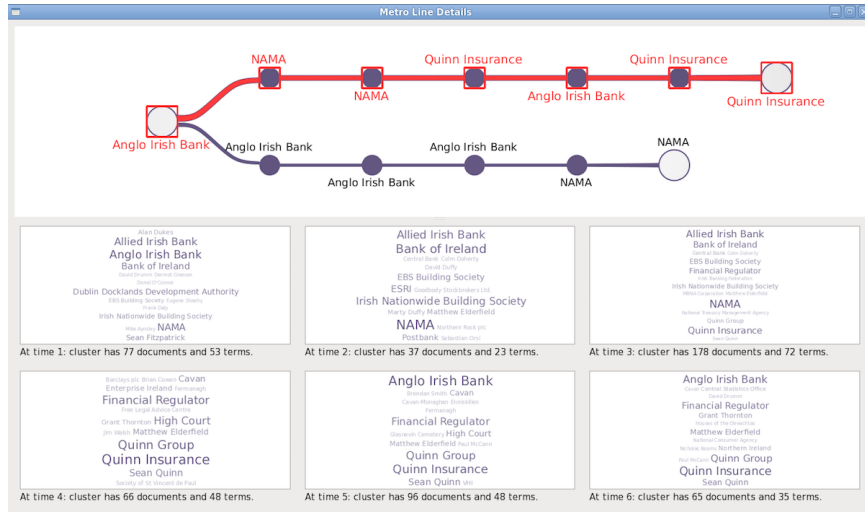


Figure 13: Metro line details view for a split event related to the banking crisis as identified in the Irish economic news data set. The split corresponds to a development in the topic where Anglo Irish Bank proposed rescue plans for Quinn Insurance.

of each cluster. For instance, we can see the changing prominence given to websites related to electronics, clothing, and furniture.

## 5.2 Economic News Data

In our second case study, we analyze a corpus of articles relating to economic news from three online news sources (RTE, The Irish Times, The Irish Independent), which were previously collected for the purpose of sentiment classification (Brew, Greene and Cunningham, 2010). We use a set of 21,746 news articles covering a period from August 2009 to April 2010. The goal of this analysis is to uncover the dominant news stories and topics that pertained to the Irish and global economic situation during that time period. To represent each article, we extract a set of terms corresponding to the named entities in the corpus: people, organizations, and geographical locations. These entities were derived from a manually curated list of 16,265 entities extracted from The Irish Independent website<sup>3</sup>. The complete data set was divided into 36 time steps, each one week in duration. Each step graph contained approximately 604 articles described by 597 terms (entities). To pre-process the data, terms appearing in less than two articles in a given step were removed, and article vectors were normalized to unit length. Given the large number of significant economic news stories reported

<sup>3</sup><http://www.independent.ie>





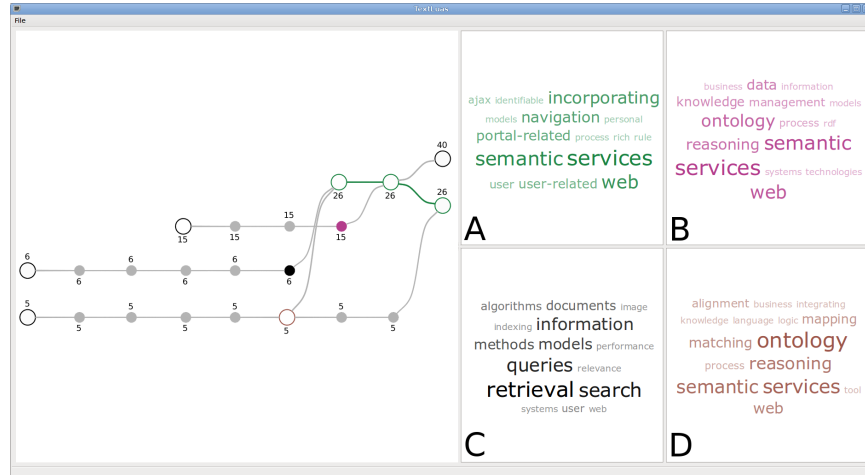


Figure 15: Diagram from Belák *et al.* which illustrates the interaction between the main ancestors of community 26 (A): 15 “semantic web” (B), 6 “web IR” (C), 5 “semantic web” (D).

sets of authors, provided that the absolute overlap between the two step clusters was at least five authors. A more detailed description of the data set and the methodology can be found in (Belák, Karnstedt and Hayes, 2010).

Frequently, scientific communities exchange members and furthermore, themes associated with each community can shift or propagate to other communities. Research communities can split into several different communities or conversely, many can merge into a single community. Many of the interesting cross-community effects are associated with simultaneous changes of the topics discussed in a community and its structure, *e.g.* a sudden emergence of a community combining topics of different disciplines may be a start of a trans-disciplinary community. When analyzing such phenomena in large dynamic networks, proper visualization and filtering techniques play a key role. The main objective for our collaborator was to observe community evolution, along with the typical life cycles in the data, and possible topic shifts in the literature that may occur.

Prior to TextLuas, the researcher used the semi-automatic generation of life cycle diagrams produced using Graphviz<sup>4</sup> and manual inspection of several large text files containing statistics about community overlaps, their characteristic themes, and other specifically-tailored measures for the analysis of cross-community phenomena. The latter tools were designed in order to understand the structure of the overlaps that existed between communities and identify the communities that caused the event. This methodology involved iterative formulation of hypotheses explaining the cross-community dynamics and successive generation of the appropriate life cycle diagrams. This process is difficult when many dynamic communities participated in a particular event. In order to publish results, the diagrams were redrawn by hand and tag clouds were generated separately in L<sup>A</sup>T<sub>E</sub>X. Examples of these figures can be found in the older publication (Belák *et al.*, 2010).

As an alternative to the manual inspection and illustration of dynamic cluster structures, Figures 15 and 16 illustrate findings by this researcher visualized by TextLuas, as discussed (Belák, Karnstedt and Hayes, 2011). A custom names file was specified for the station names based on the requirements for the user’s tasks. Figure 15 illustrates the emergence of community labeled 26 (tag cloud A), which has been identified as a potentially interesting as it was formed by distinct communities from both SW and IR fields. Moreover, the strong change of topics was subsequently identified in a second step of the community. Our collaborator wanted to examine the communities which had a significant impact on community 26, which could potentially shed some light on these dynamics. The stations that precede community 26 indicate that it was formed by SW community 5 and IR community 6 as seen by the terms in their corresponding tag clouds D and C, whereas topics like “navigation”, “personalization” and “web” suggests interdisciplinary topics of community 26. The sudden change in the second station as seen in Figure 16 naturally leads to the question: What had

<sup>4</sup><http://www.graphviz.org>

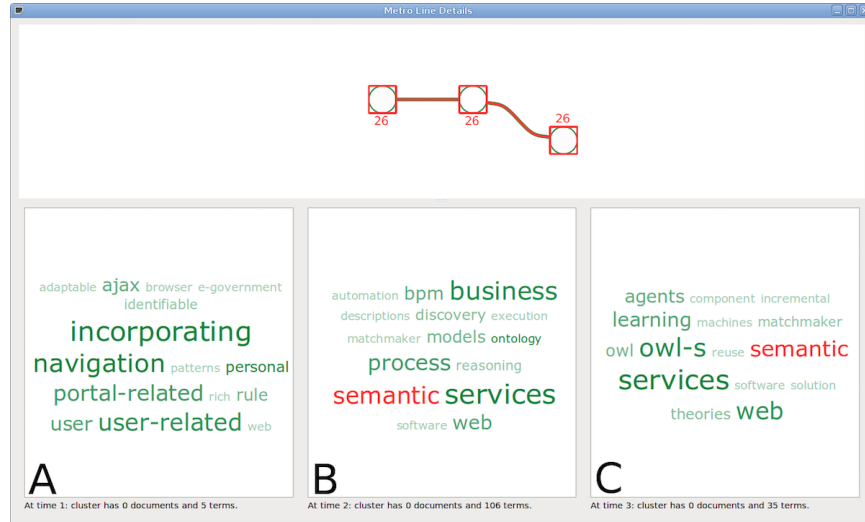


Figure 16: Diagram from Belák *et al.*, which illustrates a topic shift in community 26 from navigation-related topics towards semantic web (compare the tag cloud **A** with **B** and **C**). This corresponds with the influence of community 15.

happened? Was the community 26 influenced heavily by community 15, as suggested by a previous analytics, or was it just a false-positive and the community was rather influenced by completely new authors entering the field? In this case, the researcher can say that the topic shift was most likely due to community 15, also depicted in Figure 15, as tag cloud **B** flows into the second station of community 26. At this point, displaying community content through tag clouds was useful as it allowed the researcher to hypothesize about the causes of the cross-community events, *e.g.* change of the topics, and immediately test the hypotheses. Compared to the previous manual methodology, the use of TextLuas, which places the content *and* life cycle information in the same context, provided a faster and more efficient way to inspect the evolution of bibliographical communities.

## 6 Conclusion

Currently, TextLuas makes heavy use of linked views to show cluster content and step cluster evolution. By linked views, we mean that cluster evolution and tag cloud data is in two separate views, but they are linked by using the same color and an update to one influences the other. In future work it may be possible to integrate both tag information and cluster evolution into a single view, but further investigation is required.

TextLuas, in some senses, is scalable to large document collections. In our case studies, our visualization system scaled to collections of hundreds of thousands of time-stamped documents. However, currently TextLuas does have a limitation in that it is not as scalable when the number of timeline events increases significantly (*e.g.* highly-volatile dynamic graphs with many cluster splits, merges, births, and deaths). Additionally, as it uses color for linked highlighting, only a small number of timelines can be investigated simultaneously. In future work, we would like to look at forms of dynamic cluster aggregation or filtering that would be appropriate for the task of visualizing group evolution in highly volatile data and possible ways of increasing the number of timelines that can be compared at once. To extend the scalability of the clustering at individual time steps, problem decomposition methods could potentially be applied (Narasimhamurthy, Greene, Hurley and Cunningham, 2009).

In this paper, we presented TextLuas: a system for identifying and visualizing dynamic clusters. The contributions included a model for tracking persistent clusters across time and a system for visualizing the evolution of those dynamic clusters, in terms of both their structure *and* their associated textual content. We applied the system on two data sets, one Web 2.0 social bookmarking data set and then a collection of economic news articles, and visualized the results from the perspective of

life cycle events and cluster contents. We also solicited user feedback from researchers interested in tracking the evolution of scientific communities via bibliographic network analysis. This application suggested that TextLuas was a faster and more efficient way to inspect the dynamics of scientific communities, which is cumbersome if the information pertaining to both the content and life cycles of clusters is not integrated.

## Acknowledgment

This publication has emanated from research conducted with the financial support of Science Foundation Ireland (SFI) under Grant Numbers 08/SRC/I140 and SFI/12/RC/2289.

## References

- Asur, S., Parthasarathy, S. and Ucar, D. (2009), ‘An event-based framework for characterizing the evolutionary behavior of interaction graphs’, *ACM Transactions on Knowledge Discovery from Data (TKDD)* **3**(4), 1–36.
- Auber, D. (2003), Tulip : A huge graphs visualization framework, in P. Mutzel and M. Jünger, eds, ‘Graph Drawing Software’, Mathematics and Visualization, Springer-Verlag, pp. 105–126.
- Belák, V., Karnstedt, M. and Hayes, C. (2010), ‘Cross-community dynamics in science: How information retrieval affects semantic web and vice versa’, *arXiv* **abs/1010.4327**.
- Belák, V., Karnstedt, M. and Hayes, C. (2011), ‘Life-cycles and mutual effects of scientific communities’, *Procedia Social and Behavioral Sciences*.
- Berger-Wolf, T. and Saia, J. (2006), A framework for analysis of dynamic social networks, in ‘Proc. 12th ACM SIGKDD International Conference on Knowledge discovery and data mining (KDD’06)’, ACM, pp. 523–528.
- Blondel, V. D., Guillaume, J.-l., Lambiotte, R. and Lefebvre, E. (2008), ‘Fast unfolding of communities in large networks’, *Journal of Statistical Mechanics: Theory and Experiment* **2008**, P10008.
- Brew, A., Greene, D. and Cunningham, P. (2010), Using Crowdsourcing and Active Learning to Track Sentiment in Online Media, in ‘Proceedings of the 6th Conference on Prestigious Applications of Intelligent Systems (PAIS’10)’.
- Chakrabarti, D., Kumar, R. and Tomkins, A. (2006), Evolutionary clustering, in ‘Proc. 12th ACM SIGKDD International Conference on Knowledge discovery and data mining (KDD’06)’, ACM, New York, NY, USA, pp. 554–560.
- Chi, Y., Song, X., Zhou, D., Hino, K. and Tseng, B. (2007), Evolutionary spectral clustering by incorporating temporal smoothness, in ‘Proc. 13th ACM SIGKDD International Conference on Knowledge discovery and data mining (KDD’07)’, ACM, New York, NY, USA, pp. 153–162.
- Dhillon, I. S. (2001), Co-clustering documents and words using bipartite spectral graph partitioning, in ‘Proc. 7th ACM SIGKDD International Conference on Knowledge discovery and data mining (KDD’01)’, ACM, New York, NY, USA, pp. 269–274.
- Dhillon, I. S. and Modha, D. S. (2001), ‘Concept decompositions for large sparse text data using clustering’, *Machine Learning* **42**(1-2), 143–175.
- Falkowski, T., Bartelheimer, J. and Spiliopoulou, M. (2006), Mining and visualizing the evolution of subgroups in social networks, in ‘WI’06: Proceedings of the 2006 IEEE/WIC/ACM International Conference on Web Intelligence’, pp. 52–58.
- Frishman, Y. and Tal, A. (2004), Dynamic drawing of clustered graphs, in ‘Proc. of the 10th IEEE Symposium on Information Visualization (InfoVis ’04)’, pp. 191–198.
- Ghosh, J. (2003), Scalable clustering methods for data mining, in N. Ye, ed., ‘Handbook of Data Mining’, Lawrence Erlbaum, chapter 10.
- Görlitz, O., Sizov, S. and Staab, S. (2008), Pints: Peer-to-peer infrastructure for tagging systems, in ‘Proceedings of the 7th International Workshop on Peer-to-Peer Systems’.

- Greene, D. and Cunningham, P. (2010), Spectral co-clustering for dynamic bipartite graphs, in 'Workshop on Dynamic Networks and Knowledge Discovery (DyNAK'10)'.
- Greene, D., Doyle, D. and Cunningham, P. (2010), Tracking the evolution of communities in dynamic social networks, in 'Proc. International Conference on Advances in Social Networks Analysis and Mining (ASONAM'10)', IEEE.
- Halvey, M. J. and Keane, M. T. (2007), An assessment of tag presentation techniques, in 'WWW '07: Proc. of the 16th international conference on World Wide Web', pp. 1313–1314.
- Havre, S., Hetzler, E., Whitney, P. and Nowell, L. (2002), 'ThemeRiver: Visualizing thematic changes in large document collections', *IEEE Trans. on Visualization and Computer Graphics* **8**(1), 9–20.
- Hearst, M. A. (2009), *Search User Interfaces*, Cambridge University Press, chapter 11: Information Visualization for Text Analysis.
- Jaccard, P. (1912), 'The distribution of flora in the alpine zone', *New Phytologist* **11**(2), 37–50.
- Narasimhamurthy, A., Greene, D., Hurley, N. and Cunningham, P. (2009), 'Partitioning large networks without breaking communities', *Knowledge and Information Systems* pp. 1–25.
- Ng, A., Jordan, M. and Weiss, Y. (2001), 'On Spectral Clustering: Analysis and an Algorithm', *Advances in Neural Information Processing* **14**(2), 849–856.
- North, C. and Shneiderman, B. (2000), 'Snap-together visualization: Can users construct and operate coordinated views?', *International Journal of Human-Computer Studies* **53**(5), 715–739.
- Palla, G., Barabási, A. and Vicsek, T. (2007), 'Quantifying social group evolution', *Nature* **446**(7136), 664.
- Peng, W. and Li, T. (2011), 'Temporal relation co-clustering on directional social network and author-topic evolution', *Knowledge and Information Systems* **26**, 467–486.
- Rivadeneira, A. W., Gruen, D. M., Muller, M. J. and Millen, D. R. (2007), Getting our head in the clouds: toward evaluation studies of tagclouds, in 'CHI '07: Proc. of the SIGCHI conference on Human factors in computing systems', pp. 995–998.
- Robertson, G., Fernandez, R., Fisher, D., Lee, B. and Stasko, J. (2008), 'Effectiveness of animation in trend visualization', *IEEE Trans. on Visualization and Computer Graphics (Proc. Vis/InfoVis '08)* **14**(6), 1325–1332.
- Rosvall, M. and Bergstrom, C. (2010), 'Mapping change in large networks', *PLoS ONE* **5**(1), e8694.
- Tantipathananandh, C., Berger-Wolf, T. and Kempe, D. (2007), A framework for community identification in dynamic social networks, in 'Proc. 13th ACM SIGKDD International conference on Knowledge Discovery and Data mining (KDD '07)', ACM, pp. 717–726.
- Tufte, E. (1990), *Envisioning Information*, Graphics Press.
- Viégas, F. B. and Wattenberg, M. (2008), 'Tag clouds and the case for vernacular visualization', *Interactions* **15**(4), 49–52.
- Viégas, F., Wattenberg, M. and Feinberg, J. (2009), 'Participatory visualization with wordle', *IEEE Trans. on Visualization and Computer Graphics (InfoVis '09)* **15**(6), 1137–1144.
- Wattenberg, M. (2005), Baby names, visualization, and social data analysis, in 'Proc. of the 11th IEEE Symposium Information Visualization (InfoVis '05)', pp. 1–6.
- Yang, X., Asur, S., Parthasarathy, S. and Mehta, S. (2008), A visual-analytic toolkit for dynamic interaction graphs, in 'Proc. of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining (SIGKDD'08)', pp. 1016–1024.
- Yang, Y., Pierce, T. and Carbonell, J. (1998), A study of retrospective and on-line event detection, in 'Proc. 21st International ACM SIGIR Conference on Research and development in information retrieval', ACM, New York, NY, USA, pp. 28–36.